Plant-level Determinants of Total Factor Productivity in Great Britain, 1997-2008

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Acknowledgments

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Abstract

This paper examines the determinants of total factor productivity (TFP) using a GB plant-level dataset. It considers the role of the following four plant characteristics: internal and external knowledge; foreign ownership; multi-plant economies of scale, competition; and spatial spillovers and 'place' effects. A wide range of results are obtained, most of which confirm earlier results in the literature, such as that undertaking R&D is positively associated with TFP and most foreign ownership groups have higher than average TFP. The results also confirm the very small number of studies in the literature that have shown that the age of the plant is negatively related to TFP and therefore that vintage effects outweigh any learning-by-doing effects. The inclusion of a wide range of determinants of TFP allows comment on the relative importance of different groups of TFP determinants; knowledge creation is found to be the most important determinant of TFP (especially in manufacturing), with spatial location impacts overall the next largest determinant. Foreign-ownership is founded to be (overall) the least important determinant of TFP although this is partly the consequence of the relatively small size of the foreign-owned sector.

Keywords: productivity, plant level TFP, foreign-owned plants

JEL Classifications: C23; D24; R12

1. Introduction

Productivity (and especially the productivity of both labour and capital inputs into the production process, i.e. total factor productivity, or TFP) is widely recognised as a key driver of long-run economic growth. As Paul Krugman (1997) noted "… Productivity isn't everything, but in the long run it is almost everything"; and William Baumol similarly states that "without exaggeration in the long run probably nothing is as important for economic welfare as the rate of productivity growth" (Baumol, 1984). Using standard growth-accounting methods, large-scale country and industry studies tend to confirm the importance of TFP and its dominance in terms of explaining differences in output growth across different economies (e.g., Figure 1.2, OECD, 2003; Figure 6.3, BERR, 2008; Figure 10, Mourre, 2009; Table 2, O'Mahony and Timmer, 2009).

However, less is known about the relative determinants of productivity, and whether these differ across industry groups covering manufacturing and services. In this paper, we use plant level panel data for Great Britain covering 1997-2008 to estimate production functions at the 4-digit Standard Industrial Classification (SIC) level. These results are then aggregated into eight sectors spanning marketable output in Great Britain (four in manufacturing, and four in marketable services). Our results allow us to consider the relative importance (across these sub-sectors) of a wide range of determinants of TFP broadly grouped under the following headings: (i) internal and external knowledge creation (as represented by technical progress due to undertaking R&D in the plant, and exogenous gains over time) and its obsolescence (as represented by the age of the plant); (ii) access to better technology through belonging to a foreign-owned multinational firm; (iii) the impact of internal and multi-plant economies of scale and external market-based competition effects; and (iv) the impact of spatial spillover and 'regional' effects. To the best of our knowledge, this study is the most comprehensive and up-to-date study of its kind; indeed we have not been able to identify comparable papers in the literature that model TFP at the micro-level using such a wide range of determinants. The extant literature generally does not focus on the relative strengths of the different determinants of TFP; indeed many focus on a particular factor – such as foreign ownership – and use methods such as 'matching' that obscure the impact of other variables. That is, the purpose of such papers is to only include plants or firms in the analysis that have similar (TFP) characteristics except for the fact that one sub-set (the 'treatment' group) 'undertake' the relevant activity (e.g., they are foreign-owned) while the other sub-set (the 'control' group) do not engage in the activity (e.g., they are indigenously owned). Of course, such an approach is invariably justified on the grounds that the researcher is attempting to overcome problems associated with self-selection into the 'treatment' group, and failure to control for such effects will lead to potentially biased results. We also have to deal with endogeneity issues in this paper, and do this by treating determinants like R&D, foreign ownership and competition as endogenous through instrumenting these variables. This allows us to avoid focussing on only one variable of interest, and instead consider the wider research question of which of a range of determinants of TFP has the largest, and thus most important, impact.

The next section discusses the various determinants of TFP that have typically been considered in the literature; the emphasis is on justifying their inclusion grouped under the sub-headings set out above (leaving a discussion of previous empirical findings to when we present our own results). Section 3 sets out the modelling approach and data used to obtain estimates of plant level TFP for a majority of market-based sectors in the GB covering 1997-2008. The results are then presented in Section 4. As well as discussing the impact of individual determinants of TFP we also compare the relative overall importance of each sub-group of variables in determining overall productivity levels. Finally, we summarise our major findings.

2. The determinants of productivity[1]

2.1 Internal and external knowledge

Early approaches to understanding the micro-dynamics of productivity were particularly concerned with how the latter was related to size, the learning-by-doing effect associated with the age of the firm, and thus the likelihood of survival (cf. Jovanovic, 1982; Pakes and Ericson, 1998). Learning-by-doing models have been extended to include the investments of individual firms (particularly on intangible assets – cf. Griliches, 1981) to allow for 'active learning', thus relaxing the assumption that firm productivity levels are exogenously determined by a random draw from some stochastic distribution, and are thus constant over time (e.g., Ericson and Pakes, 1992; and Olley and Pakes, 1996). According to resource-based theories[2], firms that invest in intangible assets, such as R&D, and consequently increase their specific internal capabilities and ability to absorb external knowledge, are more likely to increase their competitiveness.[3]

Thus when estimating models of TFP, internal and external knowledge creation is usually represented as endogenous technical progress due to undertaking R&D; a time trend, measuring exogenous gains in TFP over time; and an age variable, capturing the obsolescence of knowledge. R&D is expected to have an impact on TFP through two channels. Most obviously, performing

[1]A longer version of this paper discusses these determinants in more detail. See Harris and Moffat (2013).
[2]See Penrose (1959), Wernerfelt (1984) and Barney (1991, 2001).
[3] The notion of 'absorptive capacity' was initially put forward by Cohen and Levinthal (1990), who argued that the firm's "prior related knowledge confers an ability to recognize the value of new information, assimilate it and apply it to commercial ends" and "these abilities collectively constitute what we call a firm's 'absorptive capacity'". Thus, in simple terms, absorptive capacity is the firms' ability to internalise external knowledge.

R&D may generate process innovations that allow existing products to be produced with greater efficiency (through lower costs). It may also generate product innovations which will improve TFP if the new products are produced with greater efficiency or by using better technology than existing products (i.e., an outward shift of the firm's production possibility frontier). The second channel is through the development of absorptive capacity (see Cohen and Levinthal, 1989, and especially Zahra and George, 2002, for a detailed discussion of the concept). Absorptive capacity permits the identification, assimilation and exploitation of innovations made by other firms and R&D actors, such as universities and research institutes, and is therefore also expected to lead to improvements in TFP. The notion of absorptive capacity is based on the observation that some knowledge is tacit and is difficult to acquire unless the firm is directly involved in R&D in the relevant area. These two channels through which R&D may affect TFP reflect the two 'faces' of R&D (Griffith et. al., 2004).

An 'age' variable is usually included to measure whether younger plants produce with greater efficiency and better technology than older plants (a vintage capital effect); or if through learning-by-doing productivity increases as the plant ages (e.g., Jovanovic and Nyarko, 1996). It should be noted that using the age variable is clearly a proxy for the vintage of capital and is therefore not ideally suited to capture vintage capital effects. Furthermore, the measure of the capital stock used (see Harris and Drinkwater, 2000; Harris, 2005b) should in theory be adjusted to take account of vintage effects, that occur through 'wear and tear' (i.e., deterioration of capital through use) and because new capital embodies the latest technology (leading to obsolescence in older vintages). Thus the coefficient obtained on any age variable should be an estimate of whether older plants have higher TFP because 'as plants age, managers accumulate experience, gain from learning by doing, undertake new investments, or achieve economies of scale, all of which can improve plant-level productivity' (Jensen et al., 2001). In practice though, it is unlikely that capital stock estimates are fully adjusted for obsolescence,[4] while additionally new plants have a relative advantage in adopting new technology since existing plants face sunk costs (Campbell, 1998). The strength of this 'sunk cost effect' is likely to be lower in industries characterised by low sunk costs (where entering plants can choose a mix of new and old technologies) (Lambson, 1991).

Finally a time trend is also included when modelling TFP to account for (Hicks-neutral) technical change. This is done to capture the impact on TFP of exogenous improvements in technology that are common to all plants. A priori expectations are that the importance of all three variables will vary across industry categories. In particular, these variables might be expected to be

[4] As Gittleman et al. (2006) show "… the correction of productivity growth for the vintage effect requires an estimate of the obsolescence and depreciation parameters on the basis of age data…(then) the use of capital stock in efficiency units does cause some smoothing of total factor productivity growth over time" (p. 306).

more important in high-tech industries as these tend to be more dynamic and competitive, and success will therefore depend to a greater extent on operating close(r) to the technological frontier.

2.2 Impact of foreign-ownership

Being foreign owned is argued to be related to higher levels of TFP. This is justified by the observation that, to make it worthwhile for a foreign firm to incur the costs of setting up or acquiring a plant in the domestic market, foreign firms must possess characteristics that give them a cost advantage over domestic firms (Hymer, 1976). These characteristics may include specialised knowledge about production and better management or marketing capabilities, both of which would lead to relatively high levels of TFP. Conversely, "cultural" differences between the owners of the plant and the workforce may act to lower levels of TFP in foreign owned plants, especially in the immediate period after the establishment of new 'greenfield' operations, or the acquisition of an existing plant. Dunning (1988) suggests a lack of understanding of management and labour attitudes as one such disadvantage possessed by foreign owned firms.

Furthermore, firms may undertake FDI to source technology from the host economy rather than to exploit superior technology from the home country (Driffield and Love, 2007). Plants owned by foreign owned firms that are motivated by technology sourcing rather than technology exploiting are likely to have lower TFP than plants owned by foreign owned firms that are technology exploiting (Fosfuri and Motta, 1999; Cantwell et al., 2004; Driffield and Love, 2007); thus the country of origin for FDI should matter (e.g., 'sourcing' may be more likely when the firms' headquarters are located in developing countries). Foreign-owned plants may also be expected to have lower levels of TFP if foreign-owned firms tend to keep their high value production at home and leave lower value added assembly operations to their foreign subsidiaries (Doms and Jensen, 1998). The latter will tend to employ lower-skilled workers and older technologies. It is therefore not clear from the literature whether foreign owned plants should be expected to have higher or lower TFP than domestically owned plants (as will be discussed later in Section 4, the empirical evidence is also inconclusive).

To make predictions about the relative TFP levels of 'greenfield' and 'brownfield' plants, the latter involving the merger/acquisition of an existing plant, it is helpful to consider the motives of the foreign firm when undertaking such investment. For firms undertaking FDI in order to secure access to and thereby internalise complimentary local assets, 'brownfield' investment would be the preferred form of investment (Buckley and Casson, 1998).This implies that 'brownfield' plants may well have higher TFP than 'greenfield' plants, which will not have access to these local assets,and thus will be a more attractive target for foreign-owned firms seeking to acquire plants. If so, plants acquired through 'brownfield' investment will be a self-selected (endogenous) group of the population of plants. However, there may be problems associated with 'brownfield' investment; e.g., with integration of the plant into the firm and with the establishment of trust between owners and employees (Harris, 2009). New 'greenfield' investments may also allow foreign-owned firms to introduce modern technology and modern management practices, and establish their own forward and backward supply-chains with plants that are a closer match with their own needs and requirements. Such arguments suggest that 'greenfield' plants may have higher TFP.

2.3 Economies of scale and competition effects

Internal returns-to-scale will have an impact on output but not directly on TFP as defined in equation (2) below; i.e., increases in factor inputs lead to a greater, constant, or lower increase in output via increasing, constant or decreasing scale effects (see Alexopoulos and Nakamura, 2011, section 3), but this is separate from the impact of TFP on output (see footnote 20 below for a discussion). In terms of external economies, Harris (1989) summarised the literature developed in the 1970s and 1980s on why plants belonging to multi-plant enterprises may have higher productivity (e.g., Scherer et al., 1975, 1980; Pratten, 1971; Silberston, 1972; Townroe and Roberts, 1980; Wibe, 1984). Firstly, multi-plant enterprises may benefit from economies of scale (or scope) to a greater extent than single-plant firms, especially in industries which serve a large geographic market and where transport costs are relatively high, since they are able to locate plants close to their markets. They also benefit from centralised services which assist in spreading risks, raising capital, procuring materials, supporting R&D, and engaging in sales promotion activities. Finally, because the ability to adopt the most modern technologies will be, in part, dependent upon access to information sources, single-plant firms will be at a disadvantage compared to multi-plant firms if technology is shared within multi-plant enterprises (Jarmin, 1999).

Conversely, multi-plant firms may be less efficient if they suffer from X-inefficiency (Leibenstein, 1966). This may be expected if principal-agent problems are more severe in multi-plant than single-plant enterprises. Thus the bureaucratic costs of large multi-plant firms (Chandler, 1962) as well as problems with incentives and information processing costs (Aoki, 1988) suggest that scale economies external to the plant but internal to the firm can be small or even negative. Furthermore, single-plant firms may be more innovative because they have access to a higher level of localised technical skill and knowledge than multi-plant firms. They are therefore more flexible in response to changes in demand (Kelley and Harrison, 1990). Indeed, recent literature has moved away from placing traditional economies of scale at the centre of whether single- or multi-plant firms should benefit most in terms of their productivity levels; instead more emphasis has been placed on the wider advantages of small versus large firms (especially as in recent decades products have become increasingly differentiated with shorter product cycles, implying that all firms benefit from operating smaller plants and thus concentrating on core competencies, ensuring greater flexibility, while outsourcing to other firms the production of semi-finished parts, or distribution networks, which in the 1970s and early 1980s would have traditionally been undertaken 'in-house' in larger plants – Carlsson et al., 1994).[5] Thus this newer literature comparing single-plant firms with larger multi-plant firms is concerned with the attributes of firms that are 'smaller' in terms of their organisation and managerial structures.

A measure of the concentration of output across firms, and therefore of market power, is usually included to take account of competition effects; under the assumption that the elasticity of demand does not vary too greatly across firms in an industry, this is a valid measure of competition within an industry (see, for example, Cabral, 2000). Intuitively, one would expect that greater competition will pressure firms into adopting new technologies and operating more efficiently. The theoretical premise of Nickell (1996) was that greater market competition provided firms with an incentive to reduce internal (X-) inefficiencies and therefore increase their productivity (more intense competition brings product prices closer to marginal costs, lowering rents, and this process results in higher productivity as resources and output are allocated to their most productive use).[6] Greater competition also raises the elasticity of demand. This provides greater incentives for management to improve efficiency in order to reduce prices and realise larger profits.[7] Conversely higher elasticity of demand will reduce demand for the products of poorly performing firms which charge higher prices and raise their probability of bankruptcy. Again, this provides an incentive to use improved technology. Others have shown that competition is good for innovation (Arrow, 1962; Scherer, 1980; and Aghion and Howitt, 1999).

However, it can also be argued – following Schumpeter (1943) and more recent endogenous growth theory models – that the level of competition may be inversely related to productivity if monopoly rents are required for management to invest in R&D which in turn leads to innovation and improvements in TFP (Dixit and Stiglitz, 1977; Aghion et al., 2001; Aghion and Howitt, 1992

[5] Discussion of the benefits to TFP of outsourcing, as well as empirical evidence, is presented in, for example, Aoki (1988), Coriat (1995) and Innocenti and Labory (2004). Evidence for the UK is presented in Criscuolo and Leaver (2006). Olsen (2006) provides a review of this area.

[6] Martin (1993) develops a model that shows the opposite; greater competition results in a smaller payoff from increasing marginal efficiency and therefore the less it is in the interest of the owner to put in place an incentive structure that induces the manager to reduce marginal cost. Spence (1984) similarly shows that as the number of firms in the market increases (and the expected sales of each firm decreases) then the incentive to invest in cost reduction falls.

[7] As pointed out to us by an Associate Editor, this implied relationship between competition, efficiency and profits ignores the intervening effects of economies of scope and scale. In a single-input single-output non-constant returns-to-scale production frontier, the point of maximum average product (TFP) is the point of tangency between the frontier and a ray from the origin; except in special cases like perfect competition, this is not the point of maximum profits.

and 1999; Romer, 1990; Grossman and Helpman, 1991). It has also been shown that, under some conditions, increased competition can lower the expected income of managers and therefore their effort (Hermalin, 1992). This reduced effort may be reflected in reductions in plant efficiency levels.

2.4 Spatial spillover and regional effects

Spatial spillovers or agglomeration externalities are benefits that accrue to plants from being located in the vicinity of large concentrations of other plants. Agglomeration externalities take two main forms: localisation (or Marshallian) externalities, and urbanisation (or Jacobian) externalities. The former arise due to the concentration of plants from the same industry in a given area (Marshall, 1890; Arrow, 1962; Romer, 1986). These externalities may take the form of reductions in cost from being in close proximity to upstream suppliers of inputs and downstream purchasers of outputs due to reductions in transports costs. Cost reductions may also arise due to there being a large pool of labour that has experience of working within the industry as this will reduce the costs of training. Finally, it may be hypothesised that knowledge spillovers may arise when firms jointly engage in R&D to solve common problems or as employees move between firms. This reflects an acknowledgement that a significant part of knowledge is tacit so that it does not move easily across locations due to its being embedded in individuals, firms and organisational systems (Gertler, 2003). This is a clear channel through which localisation externalities may have an impact on the technology employed in the production process and therefore TFP.

By contrast, urbanisation or Jacobian externalities are benefits that accrue to plants from diversity in the activities of plants in a particular area (Jacobs, 1970). These benefits arise due to economies of scope rather than economies of scale. One explanation for the existence of such externalities is that a more diversified industrial base (e.g., in cities) will provide access to a wider array of business services. This will be especially beneficial to smaller firms, which are unable to provide these services internally (Chinitz, 1961). Urbanisation externalities may also take the form of knowledge spillovers which arise across industries because 'the exchange of complementary knowledge across diverse firms and economic agents facilitates search and experimentation in innovation' (Van Der Panne, 2004). Assuming this innovation leads to improvements in products or processes, it should be expected that such spillovers will have an impact upon TFP. Note that this conception of knowledge spillovers contrasts with the Marshallian view that knowledge spillovers are primarily an intra- rather than an inter-industry phenomenon.

Thus there exist a wide range of variables that the previous literature suggests should be included as possible determinants of productivity. Most studies only consider a small proportion of these (as will be shown when comparing our results with those presented in the extant literature); and of course this study (due to data limitations) does not include a complete list of all likely factors that impact on TFP at the plant level.

3. Data and Model estimated

Plant-level panel data from the Annual Respondents Database (ARD)[8] is used covering 1997-2008 and all market-based sectors for Great Britain (although in this study we have omitted the following industries: those areas of agriculture, fishing and forestry covered in the ARD; mining & quarrying; utilities; construction; sales and motor vehicles repairs, wholesale and retail distribution; and financial services).[9] This data are collected by the UK's Official for National Statistics (ONS) each year as part of the Annual Business Inquiry, designed to obtain statistics for calculating the national income accounts. It is available for academic use via the UK Data Service, with stringent conditions attached to its use.[10] In our econometric analysis we weight the data using sample weights to ensure that the distribution of plants for which there is financial data are representative of the population of plants operating each year in Great Britain. Weighting is necessary both to ensure that population parameters are estimated and because of the fact that one of the endogenous variables in the model (employment) is used by the ONS as part of the stratified sampling approach to collect the ARD data; thus leading to the problem of endogenous sampling or stratification (see the appendix in Harris, 2002). Further details about the data we use are available in a data appendix in the longer version of this paper (see Harris and Moffat, 2014).

Information on intra- and extra-mural expenditure on R&D is available from the Business Enterprise R&D (BERD) database on enterprises that undertake this activity each year.[11] These data have been merged into the ARD using the unique enterprise reference codes available in both databases, and where this information was missing[12] we have used information on industry SIC codes and geographic postcodes to match respondents in the two databases. In total, based on annual data for 1997-2008 we have been able to successfully match in over 96% of the BERD respondents into the ARD (in terms of both enterprise numbers and total spending on R&D).

[8]For a detailed description of the ARD and discussion of several issues concerning its appropriate use, see Oulton (1997), Griffith (1999), and Harris (2002, 2005a). Analysis using the database covers a range of areas: cf. Disney et al. (2003a,b), Harris and Drinkwater (2000), Harris (2001, 2004), Collins and Harris (2002, 2005), Harris and Robinson (2002, 2003, 2004a,b), Harris and Hassaszadeh (2002), Harris et al. (2005), and Chapple et al. (2005).

[9] For most of these industries we have no data on capital stocks, or they are only partially covered by the ARD.

[10] More details on the UK Data service are available at http://ukdataservice.ac.uk/get-data/secure-access.aspx.

[11] Note, BERD data captures firms that 'regularly' undertake R&D, and this could potentially underestimate R&D in smaller firms and/or those in low-tech sectors.

[12] A major problem with the BERD is that the ONS use a different system of enterprise codes for some respondents.

The full set of available variables, and their definitions, is set out in Table A.1 in the appendix. Capital stocks were estimated at the plant level, linked to a benchmark estimate based on 1969 for manufacturing and 1996 for services. That is, annual 3-digit SIC real gross investment data dating from 1948 were used to calculate a benchmark capital stock for each industry, and this was then apportioned to each plant existing in the year following the benchmark year. Details on the methods used for manufacturing are set out in Harris and Drinkwater (2000); a similar approach was used for services using ONS estimates of the length-of-life of plant and machinery in each service sector. We also added (deflated) spending on the hire of plant and machinery to obtain an estimate of the total capital stock available to each plant.

The age of the plant is obtained from whichever was oldest from either the year when the plant was first observed in the ARD or from information contained in the Business Structure Database (BSD) in the ONS. The latter is especially important for services, since the ARD only includes services from 1997 (data for manufacturing is available from 1970); however, the BSD also uses information from various service sector surveys conducted by the ONS (and its predecessor, the CSO) from the 1970s and 1980' and information is available from these dating back to when plants were first included in such surveys. Harris et al. (2006) discuss these sources; for present purposes it is important to note that for most service sector plants for which there is data, the earliest observation is usually in 1977.

Single-plant status and whether the plant belonged to an enterprise operating in more than one region are obtained from using the enterprise group reference codes contained in the ARD; foreign-ownership is obtained from the ARD, and is aggregated into 3 sub-groups: US-owned, EU-owned and other foreign-owned. Attempts have been made to capture two types of spillover: agglomeration economies associated with localisation externalities due to industrial specialisation which are an intra-industry phenomenon (typically called Marshall, 1890, Arrow, 1962, and Romer, 1986, or MAR, externalities in the literature); and urbanisation economies (typically called Jacobian externalities after Jacobs, 1970 and 1986), representing diversification and therefore inter-industry spillovers.[13] The Herfindahl (1950) index of industrial concentration was also computed to take into

[13] We have experimented with different agglomeration and diversification measures (but note unlike the literature covered in Kominers, 2008, we are not measuring whether an industry is agglomerated spatially by using an aggregated *industrial* agglomeration measure; rather we are trying to capture MAR-spillovers by measuring the percentage of output located in each local authority district for each 5-digit industry). With regard to agglomeration Devereux et al. (2007) used a variable measuring the number of plants in each industry in each county-year, which is significantly correlated with our measure but which we believe to be inferior (as it ignores plant size and thus the relative amount of output produced by an industry at a particular location). For diversification, there are also several different approaches, from the simple measure used by Baldwin et al. (2010) of the population size of an area, to using a locational Herfindahl index, calculated using employment shares for disaggregated industries for each area in each year, excluding a plant's own industry (e.g. Devereux et al., 2007). These two alternative measures of diversification were strongly correlated with the one used here; the correlation with population density (we prefer this to actual population numbers to allow for the spatial size of the district) is 0.55, and with the locational Herfindahl index we had an overall

account entry (and exit) barriers that can impact on competition, with the expectation of a potentially negative influence of higher concentration on productivity. In addition, information is available on whether the plant was located in an Assisted Area, and to which Government Office region and industry (2-digit 1992SIC) it belonged.

Table 1 around here

We estimated TFP for each plant in each year based on 4-digit industry definitions.[14] In all results were obtained for 220 industry sub-groups, but for presentation purposes we report the weighted average of these results using the eight sectors set out in Table A.2. The latter were chosen based mostly on Eurostat definitions (although with some minor amendments).[15] Table 1 presents the mean (weighted) values for the variables, broken-down by sector. Medium low-tech manufacturing plants (column 3) were largest (in terms of gross output and intermediate inputs), and they were relatively old (although their capital stock was relatively small compared to other manufacturing sectors). In general manufacturing plants were larger and often older than those operating in the service sectors. Single-plant operations were more generally prevalent in manufacturing, while in services, in all but one sector, over 70% of plants belonged to enterprises operating plants in more than one region.[16]

Around 11-24% of plants in manufacturing were foreign-owned, with 'brownfield' plants somewhat more likely to be in operation, and overall EU-ownership predominating (except for high-tech manufacturing where US-ownership was a little more likely). Plants owned by firms from other foreign-owned countries were in the minority (generally across all sectors). For high-tech KI services, around 13% of plants were foreign-owned (US-ownership was more likely in this sub-group); again 'brownfield' plants were generally more common than 'greenfield' plants. In the remaining service sectors, foreign-owned plants accounted for around 9-12% of all plants (US-ownership dominating KI services and other low KI services; EU-owned more likely in low KI services), and again 'brownfield' plants were generally more in evidence (except for other low KI services where 'greenfield' US-owned prevailed).

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correlation of 0.67 (it differs by year, but never falls below 0.48). We also believe our diversification index is 'better' since using 5-digit industries and 408 local authorities, the mean of the locational H-index (subtracted from 1) was 0.98 with a standard deviation of 0.012 (i.e., most local authorities are very disaggregated); our measure has a mean of 55.3 (standard deviation of 8.1) – see Table 1.

[14] A major issue is at what level of industry disaggregation should the analysis be undertaken. To avoid the imposition of common coefficients across potentially heterogeneous industries, we have used a detailed level of disaggregation, but (as pointed out to us by a referee), such aggregation/disaggregation requires justification. We provide this in the appendix.

[15] http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an3.pdf.

[16] Regions are defined as the standard administrative (or Government Office) regions. They equate to NUTS1 definitions and there are 11 regions in Great Britain.

The average Herfindahl index of industrial concentration was generally very low across all sectors;[17] the lowest levels of concentration were in KI services, medium low-tech and low-tech manufacturing, while concentration was relatively high (on average) in other low KI services, high-tech KI services and high-tech manufacturing. Industry agglomeration was highest in the medium high and medium low-tech manufacturing sectors (covering such industries as motor vehicles, metals and shipbuilding), followed by low-tech manufacturing; it was lowest on average in KI and high-tech KI services. Diversification was slightly lower in KI services (covering higher-level business services), but generally there was little difference across the sectors covered. R&D was undertaken in around 22% of high-tech manufacturing plants, falling to 7% in low-tech manufacturing; far fewer service sector plants undertook formal R&D (some 2-3% of those in high-tech KI and KI services, and less than 1% for the other two service sectors included). Lastly, between 17-26% of plants were located in Assisted Areas, where they were eligible for help from such schemes as Regional Selective Assistance, various R&D schemes, and EU assistance (mostly from the European Regional Development Fund).

There are several approaches to estimating TFP using micro-level panel data. Del Gatto et al. (2011) and Van Beveren (2011) provide useful surveys of these different approaches to measuring TFP. The former point out that "… an array of methodologies is available, and researchers have to make a choice that, even when the estimation is only propaedeutical to the main analysis, it is likely to represent most of the story of an article" (p. 2). The analysis here is more limited as we consider only micro-econometric approaches. This allows us to concentrate on those methodologies that have become the most commonly used in recent years that rely on micro-level (e.g. firm or plant) panel data that allows the analysis of heterogeneity across enterprises and therefore a better understanding of the causes of TFP differences.

Here we define TFP using a Cobb-Douglas log-linear production function approach (including fixed-effects, α_i)[18]:

$$y_{it} = \alpha_i + \alpha_E e_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_X X_{it} + \alpha_T t + \varepsilon_{it} \quad (1)$$

[17] Dividing these numbers into 1 gives the 'numbers-equivalent' of equal-sized firms on average operating in each sector. Note, the Herfindahl index was obtained using the following formula: $Herfindahl_{jt} = \sum_i \left(y_{ij,t} / \sum_i y_{ij,t} \right)^2$ where j refers to each 4-digit industry, i refers to a plant $\in j$, t refers to year, and y refers to real gross output.

[18] The inclusion of fixed effects is necessary as empirical evidence using plant- and firm-level panel data consistently shows that plants are heterogeneous (productivity distributions are significantly 'spread' out with large 'tails' of plants with low TFP) but more importantly that the distribution is persistent – plants typically spend long periods in the same part of the distribution. Evidence using the ARD has been presented in, for example, Haskel (2000) and more recently Martin (2008). Evidence from other countries is presented in Baily et al. (1992), Bartelsman and Dhrymes (1998). Such persistence suggests that plants have 'fixed' characteristics (associated with access to different path dependent (in)tangible resources, managerial and other capabilities) that change little through time, and thus need to be modelled.

where endogenous y, e, m and k refer to the logarithms of real gross output, employment, intermediate inputs and the capital stock in plant i in time t (i= 1,…, N; t=1,…T);[19] and X_{it} is a vector of observed (proxy) variables determining TFP. In order to calculate TFP, equation (1) is estimated *directly* (e.g., Harris, et al. 2005) providing values of the elasticities of output with respect to inputs (α_E, α_M, and α_K). TFP could then be calculated as the level of (logged) output that is not attributable to factor inputs (employment, intermediate inputs and capital) – i.e., TFP is due to efficiency levels and technical progress. Thus, such a measure of TFP is equivalent to:[20]

$$\ln T\hat{F}P \equiv y_{it} - \hat{\alpha}_E e_{it} - \hat{\alpha}_M m_{it} - \hat{\alpha}_K k_{it} = \hat{\alpha}_i + \hat{\alpha}_X X_{it} + \hat{\alpha}_T t + \hat{\varepsilon}_{it} \qquad (2)$$

An alternative approach, popular in the literature, is to estimate (1) without including X_{it} on the right-hand-side of the equation, and then use (2) to obtain TFP, where X_{it} is now part of the random error term ($\hat{\varepsilon}_{\text{it}}$). Typically, $\ln T\hat{F}P_{it}$ obtained from equation (2) is then regressed on X_{it} to measure the determinants of TFP as part of a two-stage approach. Clearly, we would expect estimates of the elasticities of output (and thus $\ln T\hat{F}P_{it}$) from this two-stage approach to be biased because of an omitted variable(s) problem.

Thus equation (1) – in dynamic form with additional lagged values of output and factor inputs – was estimated using our preferred approach of system-GMM.[21] The latter allows for fixed effects, first-order autoregressive error term, and tackles endogeneity of the right-hand-side variables and selection bias by using lagged values of the endogenous variables[22] in first differences and levels as instruments (Blundell and Bond, 1998).[23] Note, as stated above, all data were also

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[19] In theory the production function should relate the flow of factor services to the flow of goods and services produced; in practice we rarely have data on capital and labour utilization at the micro-level, and this measurement error is included in ε_{it}.

[20] Using more familiar notation, TFP here is defined as A_{it} in the standard Cobb-Douglas production function:

$$Y_{it} = A_{it} E_{it}^{\alpha_E} M_{it}^{\alpha_M} K_{it}^{\alpha_K} \qquad (3)$$

and thus:

$$A_{it} = Y_{it} / (E_{it}^{\alpha_E} M_{it}^{\alpha_M} K_{it}^{\alpha_K}) \qquad (4)$$

Note, *ln*TFP is defined here by replacing lnA_{it} with the last term in equation (2). TFP is this determined by (i) the variables captured in X_{it} (which account for plants being 'on' or 'inside' the current 'best-practice' technology); (ii) the time trend (which shifts the 'best-practice' frontier generally outwards); and (iii) plant-level fixed effects and idiosyncratic shocks captured by the error term. TFP is not affected directly by returns-to-scale ($\alpha_E + \alpha_M + \alpha_K$) since any changes in the denominator on the right-hand-side of (4), as factor inputs change, is matched by changes in output, with A_{it} unchanged.

[21] An explanation for why we prefer this approach to the Olley-Pakes (1996) and Levinsohn-Petrin (2003) methods is given in the longer version of the paper.

[22] Output, intermediate inputs, labour, capital, R&D, 'brownfield' FDI and competition (the Herfindahl index) are treated as endogenous. Thus lagged (predetermined) values of these variables are used as instruments and tested for in terms of their validity (see next footnote).

[23] The validity of the instruments (i.e., that they are correlated with endogenous regressors but are not correlated with the production function error term – and hence productivity) can be tested, but system-GMM (which exploits more moments conditions than other GMM approaches) can still face the problem of weak instruments, and it is well-known by those that use the approach that the parameter estimates obtained (and the ability to pass diagnostic tests) is sensitive to the instrument set used. See also Roodman (2006) for practical guidance on applying the system-GMM approach.

weighted to ensure that the samples are representative of the population of GB plants under consideration.

4. Plant-level results

As stated in the introduction, the main focus of this paper is to derive up-to-date information on the relative importance of the different determinants of productivity. In order to avoid imposing common coefficients across industries operating with potentially disparate technologies, estimation is performed at the 4-digit SIC level.[24] The results are then aggregated into eight sectors (defined in Table A.2 by the sophistication of the technology used) by taking the weighted average (based on gross output) of the coefficients obtained at the 4-digit level *that were significantly different to zero* (standard deviations around these means are also presented to show the range of results obtained across the 4-digit SIC's for each sub-group). In this section we discuss these aggregated results, presented in Tables 2 and 3, broadly grouped under the four sub-headings used above covering: knowledge creation, foreign-ownership, economies of scale, and the impact of spatial location.[25] Finally, we aggregate the coefficients to provide a basis for determining which factors were the most important in determining TFP.

Firstly as is shown in the online appendix, the diagnostics show that the estimates obtained are economically sensible, and pass various tests of the validity of the instruments used and tests for autocorrelation. That is, all models are deemed sufficient in terms of tests for over-identification (i.e., the Hansen test of validity of the instrument set used – where instruments for the endogenous variables comprised lagged values[26] in first differences and levels, the former being used in the levels equation and the latter the first differenced equation of the system GMM model).

Tables 2 and 3 around here

4.1 Internal and external knowledge

The results obtained for the knowledge-related variables in equation (1) show that the impact on TFP of a plant having a non-zero R&D stock is positive and significant. On average, plants in

[24] The results are available in an online appendix: https://dl.dropboxusercontent.com/u/72592486/Online%20appendix.xlsx.

[25] However, it is important to emphasize that the underlying results based on all 220 industries are very diverse.

[26] Based on running a large number of regressions with different lags of the instruments for different endogenous variables, no general pattern on which lag-lengths should be used was found across both variables and the220 models estimated, other than lagged instruments starting from t – 4 or longer were generally needed for all endogenous variables (often longer in the case of instruments for the capital stock). In all instances the null hypothesis for the Hansen test is that the instruments used are exogenous (i.e., that they are correlated with endogenous regressors but are not correlated with the production function error term – and hence productivity); this null was accepted in all models.

medium high-tech manufacturing benefited the most vis-à-vis other manufacturing plants (plants in this sector with R&D had on average 23.2% higher TFP)[27]; but perhaps more surprisingly, plants in other KI services that had positive R&D stocks had the highest TFP gains. However, as was shown in Table 1, relatively few plants in other low KI services had non-zero R&D stocks; this suggests that the results for services in Tables 2 and 3 are identifying gains achieved in relatively specialised plants.

Our results also show that exogenous technical change was highest in high-tech manufacturing (3.8% p.a. increase in TFP), while medium hi-tech manufacturing also experienced a significant boost from the use of new technology (1.8% p.a.). Gains in other manufacturing sectors were around 1% p.a., while in service sectors technical change was very low, and in the case of other low KI services, technological progress was statistically negative. There are few studies against which to make any comparisons; however, using the EU KLEMS database (O'Mahony and Timmer, 2009), average TFP growth over 1997-2006 (which might be expected to be dominated by gains from new technology rather than a catch-up in efficiency levels[28]) was 5.1%, 1.4%, 2.3%, 0.5%, and 0.7% in high-tech manufacturing, medium high-tech manufacturing, medium low-tech manufacturing, low-tech manufacturing and market services respectively.[29] These results, despite being based on a growth-accounting approach and industry-level data, are broadly in line with those reported in Tables 2 – 3. The major exceptions are that our results (having controlled for various other impacts on TFP) are lower overall (we also cover the 'recession' period of 2007-2008, although its effect should be controlled for by our inclusion of a dummy for 2007-08).

Lastly, we find that higher plant age is significantly related to lower TFP; doubling plant age would decrease TFP by between 7-13%. There is some evidence that suggests that the strength of the relationship is indeed lower in industries where we might expect sunk costs to be lower, thereby lending some support to the approach taken by Lambson (1991).

In the longer version of the paper (Harris and Moffat, 2014), Tables 4 and 5 summarise the results obtained by a selection of other relevant studies of the impact of R&D and (plant) age on productivity. Despite differences in methodologies used, the results obtained here accord with those presented in the extant literature.

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[27] Parameter estimates for dummy variables need to be converted using the formula: exp($\hat{\beta}$) – 1.

[28] That is, given the persistence of heterogeneity (such that plants are expected to occupy similar positions in the distribution of TFP for long periods of time), it might be expected that relative inefficiency levels change slowly and changes in the productivity distribution are more likely in short periods to be dominated by rightward shifts caused by technical change.

[29] The sectors were not exactly the same as those used in our study (high-tech in EU KLEMS is SIC30-33; medium high-tech is SIC29, 35-35; medium low-tech is SIC23-28; low-tech is SIC15-22, 36-37; and services comprised sectors G, H, I, SIC60-64, K and O). Note we weighted individual industry results by their share in total GVA for each year 1997-2006 to obtain the overall TFP figures reported here.

4.2 Impact of foreign-ownership

In estimating equation (1), we allow for different TFP effects for US-owned, EU-owned and other foreign-owned plants, as well as for 'brownfield' and 'greenfield' plants.[30] Firstly, we find (Tables 2 and 3) that plants in most of our foreign ownership groups have higher TFP in all sectors with the exception of medium high tech manufacturing and especially high-tech KI services. This suggests that foreign-owned firms are primarily technology sourcing in these sectors rather than technology exploiting.

Brownfield US-owned plants had a TFP advantage in all sectors (ranging from 0.3-8%) while greenfield US-owned plants did even better in most sectors. Brownfield EU-owned plants had higher TFP (by 0.3-3.7%) in all manufacturing sectors and greenfield EU-owned plants had a TFP advantage in all but one manufacturing sector (medium high-tech where the TFP disadvantage was very small). The picture for EU-owned plants in services was more mixed: greenfield plants had lower TFP in high-tech KI and other low KI services while brownfield plants had lower TFP in all service sectors apart from low KI services. The TFP disadvantage for EU-owned brownfield plants in high-tech KI and KI market services was particularly large at 30.1% and 27% respectively. Reflecting perhaps the diversity of the grouping and the relatively small size of the sector, the results for other foreign-owned plants differ greatly (in quantitative terms) across sectors. Brownfield other foreign-owned plants had much lower TFP in manufacturing (being in this group was associated with an 18.7-37.2% reduction in TFP) while greenfield other-foreign-owned had higher TFP in all sectors with the exception of medium hi-tech manufacturing.

As to whether 'greenfield' or 'brownfield' investment by foreign-owned companies resulted in higher TFP, in manufacturing 'greenfield' plants generally did better within the different ownership sub-groups; 'brownfield' plants that are US-owned did better in high-tech KI services while 'greenfield' do better in this sector if other foreign-owned; 'greenfield' sites do much better in KI market services; while in other low KI market services only 'greenfield' other foreign-owned plants are relatively better. Overall we find evidence that foreign-owned plants tended to operate with superior technology, and there is evidence that plants that were set-up as new had a (cet. par.) productivity advantage (especially in manufacturing).[31]

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[30]It is important to reiterate how we define 'greenfield' and 'brownfield' when modeling of TFP using equation (1): the former is not just for the year in which the plant begins operation, but applies throughout 1997-2008 if at any time during this period a new plant was established.

[31] The longer version of this paper (Harris and Moffat, 2014, Table 6) compares our results to those in the extant literature, where similar findings are presented.

4.3 Multi-plant economies of scale and competition effects

Based on estimating equation (1), firstly we generally find (cf. Tables 2 and 3) that both manufacturing and services experienced internal decreasing returns-to-scale, although on average returns-to-scale are slightly higher in manufacturing (the exception being high-tech KI services). Thus, cet. par., as factor inputs increase, output increases less than proportionately. By contrast, most of the extant literature (see Table 7 in Harris and Moffat, 2014) suggests that others have found that manufacturing operates with increasing internal returns-to-scale, based on different approaches.

As to the impact on TFP of external economies-of-scale, our results confirm that (cet. par.) both single-plant and multi-region enterprises had higher TFP.[32] The main exception was KI market services where single plant and plants belonging to multi-region firms had lower productivity. Excluding this sector, the TFP benefit from being a single plant firm ranged from 1.9% in hi-tech and low-tech manufacturing to 10% in the other KI service sectors. The TFP advantage from belonging to a multi-region firm was generally smaller in services and ranged from 1.7% to 5.8%. This suggests that there may be 'organisation inefficiencies' associated with multi-plant firms that only operate in one region; with single-plant firms being able to exploit higher efficiency due to greater flexibility and operating in market niches, while there are additional benefits in most sectors for multi-plant firms that locate plants presumably closer to major customers and/or suppliers. This provides support for New Economic Geography and New Trade Theory models where spatial productivity effects arise from plant/firm level increasing returns to scale and indivisibilities in production, which interact with transport costs to provide benefits from proximity to markets and suppliers (Fujita et al., 1999).

Most of the extant literature (see Table 7 in Harris and Moffat, 2014) that considers multi-plant effects has concentrated on their impact on plant closure rather than TFP; previous studies, with the exception of Bernard and Jensen (2007), have shown that plants belonging to multi-plant firms are (cet. par.) more likely to be closed, but the explanation for this is usually linked to it being easier for such firms to respond to negative demand shocks by closing a plant(s) rather than scaling-down across all plants. Therefore, it is not obvious that this literature can provide solid a priori expectations for estimates of the impact of belonging to a multi-plant firm on TFP.

[32] Note, the size of the *plants* operated by single- and multi-plant enterprises may be similar (due to internal – technical – economies of scale in production); but the size of the firm is usually larger in multi-plant enterprises. Plant size is taken into account when estimating equation (1) by the inclusion of factor inputs; firm size could have been entered directly as an additional variable but for single-plant enterprises this would have resulted in enterprise and plant employment being the same (and entered twice with associated multicollinearity problems). Hence we chose to include dummy variables representing whether the plant belonged to a single-plant firm, and whether it belonged to a multi-plant firm operating in more than one region.

In terms of competition effects, Tables 2 and 3 show that we obtain the expected negative relationship in only medium low-tech manufacturing; in all other sectors, the more output is concentrated in larger firms, the higher is TFP. The latter result therefore supports the argument that monopoly rents are required to induce management to innovate. But given that there are several issues with how competition is measured,[33] this is an area that requires further research in order to provide clearer results.

Comparable existing studies of the impact of competition on productivity are provided in Harris and Moffat (2014, Table 8); different approaches are used but generally none have measured TFP effects within the production function while at the same time allowing for fixed effects, endogeneity, and including a wide array of TFP determinants. In contrast to the results obtained here, these studies generally provide clear evidence that competition does lead to higher TFP.

4.4 Spatial spillover and regional effects

Tables 2 and 3 show that we find that the effect of agglomeration externalities are positive (doubling MAR-spillovers would cet. par. increase TFP by between 1.3-7.1%). With respect to the Jacobian diversification measure, the effect of being located near to plants of different industries is negative, with a doubling of the proportion of industries nearby lowering TFP by 1.2-23% (depending on the sector). Our results also show that on average plants located in Assisted Areas (and thus eligible for industrial assistance) had lower TFP in all sectors apart from high-tech manufacturing and high-tech KI services.

As to the regional rankings (not shown in Tables 2 and 3 because of space constraints, but full results are available on request), with the South East of England as the ('frontier') benchmark region, the (cet. par.) impact on TFP of being located in a particular region is often significant and numerically important, and mostly negative. This tends to confirm that there are externalities from being in the South East region, which in general other areas do not benefit from.

Harris and Moffat (2014, Table 9) summarises some recent literature on the impact of localisation (agglomeration) and urbanisation (diversification) economies on TFP; again other studies have tended not to adequately control for fixed effects and endogeneity and to exclude a

[33] For example, it has been argued that using competition measures such as firm-level market shares and/or price-cost margins is problematic; as Brouwer and van der Wiel (2010) show increases in competition intensity can result in the reallocation of market shares from inefficient firms (with low mark ups) to efficient firms (with high mark ups), and thus increasing mark-ups are associated with more (not less) competition. Thus we have a preference for the Herfindahl index, that includes the entire distribution of market share across firms, in the expectation that this should mitigate against (although perhaps not entirely alleviate) this problem. It is also interesting to note that Martin (2010) found a significant positive correlation between TFP and firm mark-ups (firms with higher TFP charge higher mark-ups) in Chile, although he also found that over time that when competition increased mark-ups declined as productivity distributions moved to the right.

wide array of TFP determinants. Overall, and in line with the findings obtained in the present study for services, others have tended to find that localisation MAR-type economies are positive, while urbanisation economies tend to have a weaker (or even negative) impact.

4.5 Overall results

As stated in the introduction, the existing literature does not focus on the relative strengths of the different determinants of TFP; in contrast, we consider the wider research question of which of a range of determinants of TFP has the largest, and thus most important, impact. There is no single approach to aggregating coefficients within categories to allow for comparison; our preference is as follows but the weighted average of the parameter estimates displayed in Tables 2 and 3 could be aggregated in different ways.

In Table 4 (the first row of figures), 'knowledge creation' summarises the impact on TFP for each industry sub-group of undertaking R&D, experiencing annual technical change and the relative effect of the average age of plants. We are combining discrete (dummy) variables with a continuous variable (plant age), with the intention of obtaining an overall marginal effect on TFP of changes in variables. That is, for each industry sub-group we have added the average parameter estimate attached to R&D (weighted by the proportion of plants engaged in this activity) to the estimate of the average impact of technical change in that industry; we then add to this sum the parameter estimate for the *ln* age variable multiplied by the standard deviation of plant age across all industries, using a negative value for σ_x as in this instance we want to measure positive impacts on TFP (that is, we calculate the impact on the 'average' plant of moving one standard deviation to the left of the mean age of plants). The final result is multiplied by 100 to obtain a percentage,[34] showing the relative contribution to TFP of the 'average' plant in each industry based on the extent to which R&D and technical change were contributing to higher TFP, as well the impact of the age of the plant.

Table 4 around here

The second row of figures in Table 4 shows the impact on TFP of being foreign-owned, averaged over the 6 foreign-owned sub-groups used. Next we have the average impact of external economies of scale for each industry sub-group; i.e., plants that were both single-plant enterprises and those that were operating in more than region. For comparison purposes, the next row measures internal returns-to-scale (i.e., the sum of the various output elasticities for each industry in Tables 2

[34] The formula is given in the notes to Table 4; as an example, the result for the high-tech manufacturing sector is 15.9%; i.e., $100 \times [0.224\times (\exp(0.105) - 1) + 0.038 + (-0.084\times ln(3.131))]$.

and 3). This is followed in the fifth row by the impact on TFP of location. The latter is measured as the impact on the ‘average’ plant of being located in an assisted area and outside the South East (weighted by the relative importance of each region for the industry sub-group), and taking account of agglomeration and diversification effects associated with each locality (with both agglomeration and diversification measured as one standard deviation from the mean across all the various industry sub-groups covered, using a negative σ_x for diversification as the latter mostly had a negative impact on TFP in Tables 2 and 3). The last row measures the impact of competition on TFP, based on a standard deviation increase in the Herfindahl index across all the industries included. In all the calculations underlying Table 4, we include only the parameter estimates from the 220 industries that were statistically significant (setting non-significant parameter estimates to zero).

Based on these results, it can be seen that knowledge creation has by far the largest impact on TFP in manufacturing and services. The large size of this knowledge creation effect is primarily due to the impact of plant age across different sectors: as new plants enter, they employ more modern technologies which increase the level of TFP. The size of the knowledge creation effect is largest in manufacturing and in the more high-tech service sectors.

The second largest impact on TFP generally comes from spatial location (although it provides the largest effect in other low KI services). This is mainly the result of agglomeration (rather than diversification, which has a negative impact on TFP as seen above, or the spatial dummy variables). Overall, external economies-of-scale make the third largest contribution to TFP growth. Their effect is mostly driven by the coefficient on the multi-region enterprise dummy (i.e., the location of capacity in more than one region – presumably located closer to customers) rather than the coefficient on the single plant dummy. One exception to this rule is KI market services where the impact of being a single plant firm and part of a multi-region enterprise is negative. Competition contributes negatively in all sectors apart from medium low-tech manufacturing. The effect is particularly large in hi-tech manufacturing.

Being foreign-owned contributes negatively to TFP in all manufacturing sectors. Although most foreign-ownership groupings have higher than average TFP in manufacturing, those which have relatively low TFP (particularly brownfield other foreign-owned) have large negative effects which more than cancel out the smaller positive effects seen for other groups. In services, foreign-ownership contributes positively in all sectors apart from hi-tech KI (which is the result of a large negative effect for brownfield EU plants).

5. Summary & Conclusions

This paper has examined the determinants of total factor productivity (TFP) using a GB plant-level dataset. It has considered the role of the following four plant characteristics: internal and external knowledge; foreign ownership, multi-plant economies of scale and competition; and spatial spillovers and 'place' effects. Estimates were obtained using system-GMM as this allows for both fixed effects and endogenous regressors. To avoid the imposition of common coefficients across potentially heterogeneous industries, estimation was performed at the 4-digit SIC level before a weighted average of the coefficients was taken to aggregate the results to the sectoral level..

In relation to the first driver of TFP, performing R&D was found to lead to higher TFP for all sectors. The finding of a positive impact accords with a priori expectations as performing R&D should lead to both innovations and the development of absorptive capacity. The time trend (representing technical progress) was positive for all sectors except other knowledge-intensive (KI) market services. Older plants are found to have lower levels of TFP in all sectors. This suggests that the TFP impact of the obsolescence of older vintages of technology embodied in the capital of older plants outweighs any learning-by-doing effect.

In general, foreign ownership is associated with higher TFP. Medium high-tech manufacturing and KI market services sector are the major exceptions to this rule which suggests that in these sectors, foreign-ownership may be used to source knowledge whereas, in other sectors, inward FDI generally results in the exploitation of proprietary assets belonging to the investing firm. In terms of which home country of the owner does better, in manufacturing US-owned generally leads to relatively the highest levels of TFP, while in services the picture is more mixed. Generally, 'greenfield' FDI have higher TFP than brownfield FDI plants.

Turning to scale effects and competition, plants in all industries were generally found to operate under conditions of decreasing returns-to-scale (the only exception was high-tech KI services). Single plant enterprises generally had higher TFP than plants belonging to multi-plant enterprises operating in only one region, especially in services; this may reflect X-inefficiency. However, belonging to a multi-region firm led to higher TFP in six of the eight sectors considered. This suggests that economies of scale arising from membership of a multi-plant enterprise may only become important over a large geographical area (and where supplying nearby markets is important). This is of course consistent with (and provides support for) the type of models that feature in new economic geography and new trade theory (Fujita et al., 1999); i.e., spatial productivity effects arise from firm level increasing returns to scale and indivisibilities in production which interact with transport costs to provide benefits from proximity to markets and suppliers. Finally, plants operating in more concentrated industries had significantly higher TFP in most industries. To the extent that concentration is a measure of competition, this is an unexpected result and may reflect problems with the Herfindahl index as a measure of competition. On the other hand, it may reflect the need for monopoly rents to encourage innovation. The negative coefficient on this variable for the medium low-tech sector conforms more to expectations.

As expected, the coefficient on the agglomeration variable is positive for all sectors. In contrast, the diversification measure is negatively associated with TFP. As suggested by Baldwin et al. (2010) who obtain a similar result, this may suggest that congestion diseconomies are important. Plants situated in an assisted area have lower TFP for all sectors with the exception of the high-tech manufacturing and hi-tech KI services.

By aggregating within categories, it is possible to comment on the relative importance of different groups of TFP determinants. There are many different ways in which coefficients can be aggregated and the approach taken will have an impact on the results obtained. Our preferred approach suggests that knowledge creation (largely driven by capital vintage effects) is the most important determinant of TFP (especially in manufacturing), with spatial location impacts overall the next most important. Our results show that foreign-ownership is (overall) the least important determinant of TFP (although it is important to recall that this is partly the consequence of the relatively small size of the foreign-owned sector).

In terms of the long-running debate concerning whether government should attempt to directly improve the (knowledge) assets of firms or whether policy should aim to create a favourable (spatial) environment for business, our results provide evidence to support both approaches. In terms of the former, the positive impact of performing R&D suggests support for policies such as R&D tax credits. The higher TFP of (most) foreign-owned plants suggests that capital grants schemes such as Grants for Business Investment in England and Regional Selective Assistance in Scotland, which are often used to attract FDI, should have a positive impact on aggregate productivity. However, for these schemes to have this impact, they must be targeted on high-productivity FDI plants (and not foreign-owned plants that set out to 'source' better technology). Given their method of safeguarding and creating employment by assisting projects which cannot obtain funding from the private sector, there is concern that they may assist a poorer subset of plants and therefore not have the desired impact on aggregate productivity (Harris and Robinson, 2004a and 2005a; Criscuolo, et. al., 2012; Harris, 2010). Turning to the age variables, assuming that our finding that age is negatively related to TFP is driven by a vintage effect, capital grants schemes, such as those mentioned, are also supported by our results on the grounds that such schemes allow plants to upgrade their vintage of technology.

On the other hand, support can also be found from the results for policies to support the environment in which firms operate. For those industries with positive coefficients on the industry agglomeration variable, policies to encourage clusters and to facilitate collaborative research should be encouraged. However such an approach should not necessarily be concentrated on cities since greater diversification (which is more a feature in cities) has largely negative consequences.

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Appendix

Tables A1 and A2 here

Disaggregation issues

While the imposition of common coefficients on industries that operate with different technologies is generally understood to be undesirable in the production function estimation literature, the appropriate level at which the data should be disaggregated is rarely tested. The approach taken in this paper is to disaggregate by 4-digit SIC industries and therefore in this section results are provided using a simple test of whether a more aggregated approach would be appropriate. Following Elhorst (2008), let A and B denote two production functions, where $\hat{\beta}$ represents the parameters estimates and V refers to the variance-covariance, then a Wald test of the null hypothesis that the parameter estimates are the same across the two regressions is used to produce the following statistic:[35]

$$(\hat{\beta}_A - \hat{\beta}_B)'(V_A + V_B)^{-1}(\hat{\beta}_A - \hat{\beta}_B) \qquad \text{(A.1)}$$

Using the 4-digit SIC's that belong to the high-technology manufacturing sector, Table A.3 compares system-GMM regessions across pairs of industries.

Table A.3: Test statistics of null of equality of coefficients between SIC 4 digit industries

SIC	3001	3002	3210	3220	3230	3310	3320	3340	3530
3001	-								
3002	75.70***	-							
3210	188.82***	156.70***	-						
3220	187.69***	154.19***	64.83***	-					
3230	210.08***	180.49***	112.65***	88.84***	-				
3310	393.39***	435.19***	226.75***	177.91***	232.79***	-			
3320	268.73***	213.72***	105.02***	84.03***	201.54***	74.08***	-		
3330	380.04***	228.24***	120.79***	95.04***	219.89***	95.55***	49.22**	-	
3340	551.94***	388.86***	211.23***	220.08***	373.08***	159.74***	113.41***	91.08***	-
3530	302.37***	296.72***	175.28***	94.85***	140.75***	108.95***	68.11***	85.33***	93.65***
Obs.	114	248	306	251	238	395	800	120	207

*/**/*** denotes rejection of the null at the 10%/5%/1% respectively

In all cases, the null of equality of coefficients is rejected at the 95% level (there is only one pair of industries in which the null of equality of coefficients cannot be rejected at the 99% level). This therefore provides support for our approach of estimating the models at the SIC 4-digit level.

[35] Note, this approach is preferable to the use of Chow tests because of the latter's requirements that the variance of the error term is equal across the two groups.

Table A.1: Variable definitions used in BERD-ARD panel dataset for 1997-2008

Variable	***Definitions***	***Source***
Real gross output	Plant level gross output data deflated by 2-digit ONS producer price (output) indices. Data are in £'000 (2000 prices)	ARD
Real intermediate inputs	Plant level intermediate inputs (gross output minus GVA) deflated by 2-digit ONS producer price (input) indices (non-manufacturing only has a single PPI). Data are in £'000 (2000 prices)	ARD
Employment	Number of employees in plant.	ARD
Capital	Plant & machinery capital stock (£m 1995 prices) plus real value of plant and machinery hires (deflated by producer price index) in plant. Source: Harris and Drinkwater (2000, updated).	ARD
Age	Number of years plant has been in operation based on year of entry	ARD/ IDBR
Single-plant	Dummy coded 1 when plant comprises a single-plant enterprise	ARD
>1 region multiplant	Dummy coded1 if plant belongs to multiplant enterprise operating in more than 1 GB region	ARD
Greenfield US-owned	Dummy coded 1 if US-owned and newly opened during 1997-2008	ARD
Brownfield US-owned	Dummy coded 1 if US-owned and not newly opened during 1997-2008	ARD
Greenfield EU-owned	Dummy coded 1 if EU-owned and newly opened during 1997-2008	ARD
Brownfield EU-owned	Dummy coded 1 if EU-owned and not newly opened during 1997-2008	ARD
Greenfield Other foreign-owned	Dummy coded 1 if foreign-owned by another country and newly opened during 1997-2008	ARD
Brownfield Other foreign-owned	Dummy coded 1 if foreign-owned by another country and not newly opened during 1997-2008	ARD
Herfindahl	Herfindahl index (0 to 100) of industry concentration (4-digit level).	ARD
Agglomeration	% of industry output (at 5-digit SIC level) located in each local authority district-year in which plant is located – MAR-spillovers	ARD
Diversification	Proportion of 5-digit industries (from over 650) located in local authority district-year in which plant is located – Jacobian spillovers	ARD
R&D undertaken	Dummy coded1 if plant had positive R&D stock based on undertaking intramural and/or extramural R&D since 1997	BERD
Assisted Area	Dummy coded 1 if plant located in assisted area	ARD
Region	Dummy coded 1 if plant located in particular Government Office region	ARD
Industry	Dummy coded 1 depending on 1992 SIC of plant (used at 2-digit level).	ARD

[*] R&D stocks were computed using perpetual inventory method with 30% depreciation rate for the largest components of R&D spending (intra-mural current spending and extra-mural R&D). See Harris et al. (2009) for details of methods used.

Table A.2: Definitions of industrial sub-sectors (1992 Standard Industrial Classification)

High-tech manufacturing	Pharmaceuticals (SIC244); Office machinery & computers (SIC30); Radio, TV & communications equipment (SIC32); Medical & precision instruments (SIC33); Aircraft & spacecraft (SIC353)
Medium high-tech manufacturing	Chemicals (SIC24 exc. Pharmaceuticals, SIC244); Machinery & equipment (SIC29); Electrical machinery (SIC31); Motor vehicles (SIC34); Other transport equipment (SIC 35 exc. Ships & boats, SIC351, and Aircraft & spacecraft, SIC353)
Medium low-tech manufacturing	Coke & petroleum (SIC23); Rubber & plastics (SIC25); Other non-metallic (SIC26); Basic metals (SIC27); Fabricated metals (SIC28); Ships & boats (SIC351)
Low-tech manufacturing	Food & beverages (SIC15); Tobacco (SIC16); Textiles (SIC17); Clothing (SIC18); Leather goods (SIC 19); Wood products (SIC20); Paper products (SIC21); Publishing, printing (SIC22); Furniture and other manufacturing (SIC36); recycling (SIC37)
High-tech knowledge-intensive (KI) services	Telecoms (SIC642); Computer & related (SIC72 exc. Maintenance & repair, SIC725); R&D (SIC73); Photographic activities (SIC7481); Motion pictures (SIC921); Radio & TV activities (SIC922); Artistic & literary creation (SIC9231)
KI services	Water transport (SIC61); Air transport (SIC62); Legal, accountancy & consultancy (SIC741 exc. Management activities of holding companies, SIC7415); Architecture & engineering (SIC742); Technical testing (SIC743); Advertising (SIC744)
Low KI services	Hotels & restaurants (SIC55); Land transport (SIC60); Support for transport (SIC63); real estate (SIC70); Renting machinery (SIC71); Maintenance & repair of office machines (SIC725); Management activities of holding companies (SIC7415); Labour recruitment (SIC745); Investigation services (SIC746); Industrial cleaning (SIC747); Packaging (SIC7482); Secretarial services (SIC7483); Other business services (SIC7484); Sewage & refuse (SIC90)
Other low KI services	Postal services (SIC641); Membership organisations (SIC91); Other entertainment services (SIC923 exc. Artistic & literary creation, SIC9231); News agencies (SIC924); Sporting activities (SIC926); Other recreational activities (SIC927); Other services (SIC93).

Table 1: Mean (weighted) values 1997-2008, by sector[a]

Sector	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real gross output	1025.6	1135.8	1717.5	1151.5	335.8	1074.5	340.3	248.6
Real intermediate inputs	575.9	692.8	908.6	628.4	97.0	260.7	192.5	137.2
Capital	0.4	0.4	0.2	0.2	0.0	0.1	0.0	0.0
Employment	22	22	21	20	4	12	8	6
Age	4.5	5.2	6.7	6.5	2.9	6.7	4.7	4.5
Single-plant	0.252	0.259	0.345	0.291	0.192	0.415	0.100	0.153
>1 region multiplant	0.504	0.499	0.519	0.506	0.716	0.529	0.768	0.729
Greenfield US-owned	0.028	0.025	0.008	0.008	0.036	0.015	0.014	0.056
Brownfield US-owned	0.056	0.070	0.027	0.030	0.034	0.028	0.021	0.024
Greenfield EU-owned	0.025	0.031	0.020	0.016	0.016	0.015	0.029	0.003
Brownfield EU-owned	0.055	0.075	0.074	0.036	0.021	0.021	0.051	0.006
Greenfield Other foreign-owned	0.010	0.012	0.005	0.005	0.007	0.004	0.003	0.000
Brownfield Other foreign-owned	0.030	0.024	0.023	0.017	0.012	0.008	0.012	0.002
Herfindahl	0.106	0.093	0.055	0.068	0.114	0.018	0.089	0.170
Agglomeration	0.393	0.599	0.573	0.516	0.222	0.198	0.302	0.264
Diversification	0.631	0.633	0.585	0.600	0.624	0.573	0.616	0.614
R&D undertaken	0.224	0.190	0.096	0.069	0.033	0.021	0.002	0.002
Assisted Area	0.189	0.213	0.260	0.216	0.171	0.182	0.182	0.188
N of plants	15,529	49,127	58,128	94,611	113,878	93,791	1,886,325	214,439

[a] See Table A.1 for definitions.

Table 2: Long-run weighted systems GMM production function, manufacturing sectors[ab], 1997-2008

	Hi-Tech	Medium Hi-Tech	Medium Low-Tech	Low-Tech
ln Intermediate Inputs	0.502	0.562	0.558	0.551
	(0.155)	(0.146)	(0.166)	(0.170)
ln Employment	0.334	0.266	0.296	0.273
	(0.137)	(0.120)	(0.173)	(0.152)
ln Capital	0.139	0.156	0.136	0.154
	(0.056)	(0.103)	(0.081)	(0.116)
time trend	0.038	0.018	0.011	0.007
	(0.052)	(0.024)	(0.018)	(0.017)
R&D	0.105	0.209	0.065	0.075
	(0.110)	(0.156)	(0.148)	(0.118)
ln Age	-0.084	-0.097	-0.132	-0.131
	(0.082)	(0.138)	(0.099)	(0.124)
Single Plant	0.018	0.030	0.064	0.018
	(0.100)	(0.078)	(0.143)	(0.151)
Multi-region Firm	0.034	-0.014	0.039	0.038
	(0.125)	(0.107)	(0.070)	(0.122)
Greenfield USA	0.035	-0.007	0.088	0.067
	(0.136)	(0.073)	(0.550)	(0.113)
Brownfield USA	0.003	0.020	0.031	0.036
	(0.150)	(0.250)	(0.147)	(1.033)
Greenfield EU	0.014	-0.001	0.164	0.032
	(0.151)	(0.123)	(1.986)	(0.156)
Brownfield EU	0.019	0.006	0.034	0.003
	(0.146)	(0.198)	(0.218)	(0.329)
Greenfield Other Foreign-	0.018	-0.008	0.093	0.001
Owned	(0.148)	(0.183)	(0.487)	(0.104)
Brownfield Other Foreign-	-0.207	-0.218	-0.465	-0.266
Owned	(0.364)	(0.876)	(4.930)	(1.177)
ln Agglomeration	0.034	0.033	0.021	0.043
	(0.068)	(0.047)	(0.080)	(0.071)
ln Diversification	-0.055	-0.194	-0.012	-0.021
	(0.133)	(0.195)	(0.120)	(0.215)
ln Herfindahl	0.092	0.025	-0.014	0.019
	(0.116)	(0.109)	(0.175)	(0.197)
Assisted Area	0.016	-0.004	-0.012	-0.003
	(0.110)	(0.049)	(0.064)	(0.113)
Dummy 2007-08	0.023	-0.034	-0.020	-0.047
	(0.170)	(0.154)	(0.088)	(0.182)
Intercept	3.384	3.401	2.946	3.182
	(1.074)	(0.978)	(1.093)	(1.339)
9 region dummies	Yes	Yes	Yes	Yes
Returns to scale	0.975	0.985	0.990	0.977
Number of plants	2,939	8,265	7,726	14,627
Observations	7,407	22,026	17,462	39,600

[a] See Table A.2 for definition. [b] Standard deviations of coefficients from individual 4-digit SIC industries in parentheses (the detailed results are available to download – see footnote 22).

Table 3: Long-run weighted systems GMM production function, service sectors[ab], 1997-2008

	Hi Tech KI	KI Market	Low KI	Other KI
ln Intermediate Inputs	0.568	0.419	0.612	0.491
	(0.150)	(0.255)	(0.202)	(0.115)
ln Employment	0.324	0.432	0.244	0.300
	(0.214)	(0.240)	(0.143)	(0.162)
ln Capital	0.118	0.137	0.120	0.174
	(0.133)	(0.095)	(0.098)	(0.033)
time trend	0.004	0.003	0.004	-0.008
	(0.022)	(0.015)	(0.024)	(0.028)
R&D	0.005	0.014	0.107	0.336
	(0.204)	(0.077)	(0.263)	(0.326)
ln Age	-0.126	-0.090	-0.083	-0.070
	(0.148)	(0.101)	(0.141)	(0.183)
Single Plant	0.101	-0.099	0.095	0.091
	(0.157)	(0.381)	(0.216)	(0.151)
Multi-region Firm	0.017	-0.029	0.057	0.030
	(0.291)	(0.402)	(0.181)	(0.161)
Greenfield USA	0.006	0.157	0.047	0.009
	(0.326)	(0.186)	(0.212)	(0.321)
Brownfield USA	0.077	0.072	0.041	0.015
	(0.425)	(0.205)	(0.210)	(0.270)
Greenfield EU	-0.125	0.080	0.041	-0.034
	(0.204)	(0.147)	(0.305)	(0.151)
Brownfield EU	-0.369	-0.315	0.058	-0.021
	(0.517)	(0.588)	(0.203)	(0.081)
Greenfield Other Foreign-Owned	0.044	0.412	0.021	0.096
	(0.557)	(0.644)	(0.254)	(0.000)
Brownfield Other Foreign-Owned	-0.028	0.041	0.231	0.089
	(0.188)	(0.323)	(0.556)	(0.312)
ln Agglomeration	0.013	0.020	0.037	0.071
	(0.077)	(0.038)	(0.067)	(0.051)
ln Diversification	-0.040	-0.130	-0.089	-0.230
	(0.416)	(0.226)	(0.311)	(0.311)
ln Herfindahl	0.021	0.025	0.023	0.045
	(0.248)	(0.062)	(0.186)	(0.325)
Assisted Area	0.005	-0.016	-0.013	-0.014
	(0.085)	(0.134)	(0.096)	(0.038)
Dummy 2007-08	-0.105	-0.012	-0.083	0.001
	(0.114)	(0.118)	(0.155)	(0.143)
Intercept	2.554	3.266	2.771	3.386
	(1.328)	(1.531)	(1.665)	(0.891)
9 region dummies	Yes	Yes	Yes	Yes
Returns to scale	1.010	0.988	0.976	0.964
Number of plants	16,419	15,305	104,393	11,473
Observations	36,648	34,968	318,597	32,062

[a] See Table A.2 for definition. [b] Standard deviations of coefficients from individual 4-digit SIC industries in parentheses (the detailed results are available to download – see footnote 22).

Table 4: Relative importance of different TFP effects based on equation (1) (figures are percentages except internal returns-to-scale)

	Manufacturing				Services				All sectors
Impact	High-tech	Medium high-tech	Medium low-tech	Low-tech	High-tech KI	KI market	Low KI market	Other low KI market	
Knowledge creation[a]	15.9	17.3	16.8	16.2	14.8	10.6	9.9	7.3	11.7
Foreign-ownership[b]	-0.3	-0.3	0.0	-0.2	-0.5	0.3	0.9	0.1	0.5
External economies-of-scale[c]	2.2	0.1	4.3	2.5	3.3	-5.4	5.5	3.7	3.6
(Internal economies-of-scale	0.975	0.985	0.990	0.977	1.010	0.988	0.976	0.964	0.98
Spatial location[d]	7.0	9.7	6.0	7.4	3.9	4.2	7.8	14.5	7.5
Competition[e]	-12.4	-3.4	1.9	-2.6	-2.8	-3.4	-3.1	-6.1	-2.9

[a] I.e., $100 \times \left[\sum_{i=1}^{n} \frac{R\&D_i}{n} \times \left(\exp\left(\hat{\beta}_{R\&D}\right) - 1\right) + \hat{\beta}_{time} + \left(\hat{\beta}_{\ln Age} \times -\ln(\sigma_{Age})\right) \right]$, where *R&D* and *Age* are defined in Table A.1; $\hat{\beta}$ refers to the parameter estimates reported in Tables 2 and 3; *i* refers to plant *i* across all *n* plants in the industry sub-group (1997-2008); and σ refers to the standard deviation across all plants included in Tables 2 and 3 (note σ_{Age} = 3.131).

[b] I.e., $100 \times \left[\sum_{k=1}^{6} \left(\exp(\hat{\beta}_k) - 1 \times \sum_{i=1}^{n} \frac{FO_{ik}}{n} \right) \right]$, where the *k* foreign-owned sub-groups are defined in Table A.1.

[c] I.e., $100 \times \left((\exp(\hat{\beta}_{Single-plant}) - 1) \times \sum_{i=1}^{n} \frac{Single_i}{n} + (\exp(\hat{\beta}_{>1region}) - 1) \times \sum_{i=1}^{n} \frac{>1region_i}{n} \right)$.

[d] I.e., $100 \times \left[\left(\exp\left(\hat{\beta}_{Assisted}\right) - 1 \right) \times \sum_{i=1}^{n} \frac{Assisted_i}{n} + \left(\left(\sum_{r=1}^{10} (\exp(\hat{\beta}_r^i) - 1) \times \bar{X}_r^i \right) \right) + \left(\hat{\beta}_{\ln agglom} \times \ln(\sigma_{agglom}) \right) + \left(\hat{\beta}_{\ln diver} \times -\ln(\sigma_{diver}) \right) \right]$.

where *Assisted*, *Agglom* and *Divers* are defined in Table A.1; b_r^i is the parameter estimate in Table 2 or 3 for region *r* and industry sub-group *i*, and $\bar{X}_r^i$ is the proportion of plants in the industry sub-group located in each region *r*; σ refers to the standard deviation across all plants included in Tables 2 and 3 (note σ_{agglom} = 5.676 and σ_{diver} = 1.266).

[e] I.e., $100 \times \left[\hat{\beta}_{\text{Herf}} \times -\ln(\sigma_{\text{Herf}}) \right]$. Note, σ_{Herf} = 3.846.